Generating science-based growth: an econometric analysis of the impact of organizational incentives on university-industry technology transfer.

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Abstract:

In recent years, there has been a rapid rise in commercial knowledge transfers from universities to practitioners or university/industry technology transfer (UITT), via licensing agreements, research joint ventures, and startups. In a previous study in 1999, the authors outlined a production function model to assess the relative efficiency of UITT and conducted field research to identify several organizational factors that could enhance the effectiveness of university management of intellectual property portfolios. This paper extends this framework and evaluates the impact of organizational incentives on the effectiveness of UITT. It is found that universities having more attractive incentive structures for UITT, i.e. those that allocate a higher %age of royalty payments to faculty members, tend to be more efficient in technology transfer activities. University administrators who wish to foster UITT should be mindful of the importance of financial incentives.

Keywords: university/industry technology transfer | stochastic frontier estimation | organizational incentives | finance | commercial knowledge transfer

Article:

1. Introduction

In recent years, there has been a rapid rise in commercial knowledge transfers from universities to practitioners or university/industry technology transfer (UITT), via such mechanisms as licensing agreements, research joint ventures, and university-based startups. Since university management of intellectual property portfolios is a relatively new phenomenon at most academic institutions, there is considerable uncertainty among administrators regarding optimal organizational practices within the technology transfer infrastructure. The end result is all research universities are searching for ways to maximize the efficiency of UITT, that is the private financial returns that accrue to the university from these commercialization activities.

The ability of universities to effectively manage intellectual property portfolios also has important policy implications, since governmental officials increasingly view university technology transfer as a mechanism for stimulating regional growth and development.1 That is, UITT activities may also generate significant social returns, i.e. local technological spillovers that benefit firms and consumers in the vicinity of the university, or others who benefit from the new products and processes that arise from more rapid technological diffusion.

Unfortunately, there is little empirical evidence that would serve to guide university administrators who manage the UITT process. The purpose of this study is to fill this gap, based on quantitative and qualitative, field-based evidence. Measures of relative productivity are constructed from benchmarking surveys conducted by the Association of University Technology Managers (AUTM), which contain information on UITT inputs and outputs. We complement our econometric analysis with insights from field interviews at five research universities in two regions of the USA. Essentially, we use the qualitative work to specify the arguments of the production function and determinants of the deviation from the efficiency frontier.

The remainder of this paper is organized as follows. Section 2 discusses our qualitative, field-based research, which enabled specification of the UITT production function and identification of some of the organizational factors that may explain some of the variation in UITT performance across universities. Section 3 outlines the econometric framework that is used to assess and explain variations in relative UITT productivity. Section 4 describes the data and empirical results. Conclusions and suggestions for additional research are presented in the final section.

2. Qualitative evidence relating to UITT productivity

In order to improve our understanding of the UITT production process, we conducted extensive field interviews, which are described in great detail in Siegel et al. (2003). An inductive approach was employed during this exercise, since it was not clear from the literature how one would specify a UITT production function or which institutional and organizational factors are most relevant, in terms of explaining why some universities outperform others.

The qualitative data consist of information collected during structured, in-person interviews of directors of university technology transfer offices (TTOs) and other university technology administrators (e.g. Vice-provost for Research), entrepreneurs and managers whose firms have transferred technologies, and academic scientists at five major (classified by the Carnegie Foundation as 'Research-One') research universities in the Southwest and Southeast USA.2

Table 1 presents some information on the five universities that were examined. This set includes private and public universities, land grant institutions, and universities with and without a medical school. There is also considerable variation with respect to size and age of the TTO, and extent of licensing activity. The bottom panel of Table 1 presents a comparison of mean values of key variables (average annual number of licensing agreements, licensing revenue, TTO staff and age) for the five institutions visited, and for 113 universities whose administrators completed a comprehensive UITT survey conducted by the Association of University Technology Managers (AUTM). Although the five institutions generate below average licensing revenue, they are quite similar to the average AUTM respondent along the other dimensions. These findings lend credence to our assertion that the universities in our field study are representative institutions, with respect to UITT.

Table 1 Characteristics of the five universities in the qualitative study and comparison of mean values of key variables with full statistical sample of 113 universities (1991–1998)

	University A	**University B**	**University C**	**University D**	**University E**
Organizational status	Private	Public	Public	Public	Public
Medical School	Yes	Yes	No	No	Yes
Land Grant Institution	No	No	Yes	No	Yes
TTO established in	1984	1985	1982	1985	1988
STAFF	14.2	11.5	11.1	2.9	8.5
LICENSE1	28.1	19.0	26.1	3.4	12.0
LICENSE2	1213.2	773.3	1535.7	382.7	177.0

Source: Association of University Technology Managers (1999).

Table 1 Characteristics of the five universities in the qualitative study and comparison of mean values of key variables with full statistical sample of 113 universities (1991–1998)

Mean values of key variables (1991–1998)			
Variable name	**Description**	**Five universities in field study**	**113 universities in statistical sample**
LICENSE1	Average annual licensing agreements	17.7	16.1
LICENSE2	Average annual licensing revenue ($000)	816.4	1937.5
STAFF	Average annual TTO employees	9.6	9.4
AGE	Numbers of years since TTO was established (as of 1996)	11.1	13.2

At each university, we interviewed academic scientists, TTO directors, and top-level research administrators. Within the surrounding region, we also met with entrepreneurs, directors of business development, intellectual property managers and other research executives of large companies, and executives of patent management firms and non-profit organizations with an interest in UITT. All in all, we conducted 55 interviews: 20 managers and entrepreneurs, 15 administrators (including the 5 TTO directors), and 20 scientists. During these 55 face-to-face meetings, 98 individuals were interviewed, since multiple respondents were present during a number of meetings.

In order to derive some broad conclusions from the information provided by our interviewees, we conducted a quantitative analysis of the qualitative data, based on methods outlined in Miles and Huberman (1994). This involved carefully reading each transcript and identifying specific themes that emerged from responses to open-ended questions regarding UITT. Comments relating to a particular theme were then coded, which enabled us to generate a set of frequency tables, containing percentages of respondents who identified a particular theme relating to their perceptions regarding outputs and barriers to effective UITT. Such percentages were then computed separately for each type of respondent (i.e. university administrators, managers/entrepreneurs, and academic scientists). Some of the inferences we make in the remainder of this paper regarding institutional and organizational factors are based on these figures.3

2.1 Inputs and outputs

With respect to the specification of the UITT production function, there were three key stylized facts derived from the field research. The first is that although faculty members working on a federal research grant are required to disclose inventions to the university technology transfer office (TTO), some researchers do not follow this practice and the rule is rarely enforced by their university. This aberrant behaviour on the part of faculty members and lack of monitoring on the part of administrators highlights the importance of the labour input of TTO staff in simply eliciting disclosures and thus, increasing the potential pool of potential technologies for licensing.

Our field research also revealed that the importance of patents in this process is often overstated. Specifically, we discovered that many firms license technologies long before the university patents them, if they are patented at all. This early licensing occurs for several reasons. First, patent protection may not be viable or critical for a particular type of technology. For instance, patents are not important in the computer software industry or in the design of integrated circuits. Second, firms may have considerable faith in the scientist's ability or reputation, or because the inventor has a longstanding financial relationship with the firm.4 Finally, some firms (especially younger, more entrepreneurial companies) are anxious to lock-in promising embryonic technologies at a low price. These findings imply that a critical input in this process is invention disclosures, which constitute the pool of available technologies for licensing.

A third key stylized fact culled from our interviews relates to the importance of (external) intellectual property (IP) lawyers in UITT. Some institutions use IP lawyers to help them obtain copyrights and in various aspects of patenting and licensing, especially in support of prosecution, maintenance, litigation, and interference. Indeed, it is quite common for universities to devote substantial resources to the maintenance and re-negotiation of licensing agreements due to the embryonic nature (e.g. uncertainty) of the technologies and to the fledgling nature of many of the firms that license university-based technologies.

In sum, our qualitative research leads us to conjecture that the following are ‘inputs’ to UITT:

1. Invention disclosures (a proxy for the set of available technologies for licensing).
2. Labour employed by the TTO.
3. Legal fees (external) incurred to protect the university's intellectual property.5

Discussions with university administrators—the ‘producers’ in our model—were also helpful in determining the relevant set of outputs. These officials perceive that licensing activity is by far the most critical output, although they disagree as to whether revenue or some measure of the flow of licensing deals (e.g. average annual number of licensing agreements) is more important. Specifically, we found that 87% of the administrators viewed licensing revenue as their relevant output; while 67% mentioned the number of licensing transactions. Given these qualitative findings, we use licensing revenue and the number of licensing agreements consummated as our proxies for output in the UITT production function.

2.2 Environmental factors

Relative efficiency in UITT is also likely to be related to environmental factors, such as the presence of a medical school on campus. A recent study reports that over 60% of MIT's university licenses result from a biomedical invention.6 Other environmental variables might include measures of regional economic growth and R&D activity of local companies, which allow us to control, albeit imperfectly, for financial and technological factors that influence the ability of firms to sponsor R&D at the university and the existence of technological agglomeration externalities. Numerous authors report evidence of such spillover effects. Jaffe et al. (1993) report that patents generated within the same state and SMSA are more likely to be cited by firms in the same state or SMSA. Audretsch and Stephan (1996) analyse interactions between academic scientists and local firms and conclude that such linkages play an important role in promoting innovation in biotechnology.

2.3 Institutional and organizational factors

Our qualitative analysis was initiated on the proposition that managerial practices in UITT may be important in explaining variation in relative performance, since this activity is fertile ground for potential organizational conflict. We conjecture that such discord is likely to arise because academic scientists, university administrators, corporate managers, and entrepreneurs have heterogeneous goals and objectives, which they pursue from the perspective of different organizational cultures. For instance, academics are primarily motivated by recognition within the scientific community, which requires that they quickly disseminate knowledge in published form. This form of disclosure conflicts with goal of firms and entrepreneurs to maintain proprietary control over knowledge in order to maximize the financial return on investment in knowledge.

The bureaucratic culture of the university is similarly at odds with the organizational culture of most entrepreneurial firms, which value timeliness, speed, and flexibility. Reflecting these cultural values, numerous managers stressed the importance of time to market and concomitant first mover advantages as critical success factors of UITT. On the contrary, university administrators (working through the TTO) typically have little incentive to dramatically accelerate the commercialization process. Not surprisingly, they were focused on following all the appropriate rules and procedures, in case they are accused of ‘giving away’ lucrative university-based technologies.7

The field research revealed that the most critical barriers to effective UITT are those related to informational and cultural barriers between universities and firms, the responsiveness of universities to the needs of firms and entrepreneurs, and reward systems for faculty involvement in UITT. Although it is difficult to construct precise measures of these factors, we hypothesize that three variables may serve as useful proxies, which we describe in the remainder of this section.

Our field evidence implies that there may be a learning effect, with respect to formal university management of intellectual property. If organizational learning occurs, universities with more experience in formal management of UITT may be more efficient than comparable universities with less experience. Thus, we also construct a measure of the age of the TTO (AGE).

The interviews revealed that organizational incentives for UITT might also be relevant. Two factors are likely to affect the propensity of faculty members to become involved in UITT. The first is the department and university's promotion and tenure (P&T) policies, which typically do not reward such activity. Indeed, some academics asserted that such activity was penalized in P&T, based on an opportunity cost argument. A second factor that is hypothesized to influence faculty involvement in UITT relates to pecuniary rewards. This is the university's royalty and equity distribution formula, which determines the percentage of the licensing royalty (or equity) that is allocated to faculty members who transfer technologies.

Unfortunately, we do not have any systematic measures across universities of the level of receptiveness to UITT activity in P&T policies. However, we were able to collect information on royalty percentages at numerous universities. The most common distribution formula is to divide royalties equally between the academic inventor, the inventor's department, and the rest of the university. Thus, we constructed a variable ROYALTY, which denotes the percentage of licensing royalties (or equity) allocated to faculty members at a given institution.8 As noted in Friedman and Silberman (2003), there is considerable variation in the inventor's share of licensing royalties, ranging from a low of 22.8% at Arizona State University to a high of 88.8% at Carnegie Mellon. The corresponding numbers at MIT, Stanford, and Columbia (three universities that generate substantial UITT) are 27.1%, 27.1%, and 50.0%, respectively.

We also conjecture that organizational structure may be relevant, in terms of making universities more responsive to the needs of firms who commercialize university-based technologies. There appear to be two basic models for managing licensing offices: a centralized or decentralized structure. For instance, MIT and Stanford have a single licensing office for the entire university. A more extreme form of centralization is when there is one licensing office for all the public universities within a state (e.g. the State University of New York (SUNY)). Some public universities have established centralized foundations to manage licensing, such as the Wisconsin Alumni Research Foundation (WARF), which holds the most valuable stem cell research patent.

Bercovitz et al. 2001) provide an excellent example of decentralized licensing. They note that Johns Hopkins has separate licensing offices for its medical school, Applied Physics Laboratory, and the remainder of the university. Another form of decentralization involves universities outsourcing the licensing function. One of the organizations we visited, Research Corporation Technologies, based in Tucson, Arizona, has managed technology transfer licensing for several universities, including Michigan State.

3. Measurement and analysis of relative productivity

Our framework for constructing measures of relative productivity is stochastic frontier estimation, which was developed independently by Aigner et al. (1977) and Meeusen and Van den Broeck (1977). This method generates a production (or cost) frontier with a stochastic error term that consists of two components: a conventional random error and a term that represents deviations from the frontier, or relative inefficiency.

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Assume that the production function can be characterized as

$$y_i = \mathbf{X}_i\beta + \_i$$

where the subscript i refers to the ith university, y represents licensing output, $\mathbf{X}$ denotes a vector of inputs, β is the unknown parameter vector, and _ is an error term that consists of two components, $\epsilon_i = (V_i - U_i)$, where U_i is a non-negative error term representing technical inefficiency, or failure to produce maximal output given the set of inputs used, and V_i is a symmetric error term that accounts for random effects. Thus, we can rewrite equation (1) as

$$y_i = \mathbf{X}_i\beta + V_i - U_i$$

Consistent with Aigner *et al.* (1977), we assume that the U_i and V_i have the following distributions:

$$V_i \sim \text{i.i.d. } N(0, \sigma_v^2)$$
$$U_i \sim \text{i.i.d. } N^+(0, \sigma_u^2), \quad U_i \geq 0$$

That is, the inefficiency term *Ui* is assumed to have a half-normal distribution; i.e. universities are either 'on the frontier' or below it.9 Jondrow *et al.* (1982) specify a functional form for the conditional distribution of [*Ui/(Vi − Ui)*], the mean (or mode) of which provides a point estimate of *Ui* .

An important parameter in stochastic frontier models is $\gamma = \sigma_u^2/(\sigma_v^2 + \sigma_u^2)$, the ratio of the standard error of technical inefficiency to the standard error of statistical noise, which is bounded between 0 and 1. Note that $\gamma = 0$ under the null hypothesis of an absence of inefficiency, which would imply that all of the variance in the observed error term can be attributed to statistical noise.

An important extension of the stochastic frontier literature (Pitt and Lee, 1981) has been the ability to incorporate determinants of technical inefficiency into these models. This extension is crucial to our analysis, since a chief goal of our study is to 'explain' deviations from the frontier (i.e. relative inefficiency in UITT). Consistent with Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) we conjecture that the Ui are independently distributed as truncations at zero of the $N(mi, \sigma 2\ u)$ distribution with

$mi = \mathbf{Z}i\theta$

where **Z** is a vector of environmental, institutional, and organizational variables that are hypothesized to influence relative efficiency and θ is a parameter vector.10

As shown in Battese and Coelli (1995), simultaneous estimation of the production frontier and inefficiency equations (equations (1a) and (2)) by maximum likelihood methods generates estimates of the parameter vectors β and δ, which we can use to compute estimates of relative productivity. The authors also note that this method is preferable to a two-stage approach, which involves computing estimates of relative productivity and then running OLS regressions on a set of determinants of establishment-level relative inefficiency. The problem with the two-stage approach is that it yields inconsistent estimates, since the inefficiency effects in the first stage of the model are assumed to i.i.d., while in the second stage they are hypothesized to be a function of university-specific factors.

Two critical issues arise in the context of production function estimation. The first is whether to employ non-parametric methods (e.g. data envelopment analysis (DEA)) or parametric estimation procedures, such as the stochastic frontier method.11We have already resolved this issue in favour of the stochastic frontier approach, given our interest in conducting hypothesis tests relating to the production function parameters (e.g. estimating returns to scale) and the determinants of relative productivity (e.g. assessing the relative importance of institutional and organizational factors).

A second issue, given our choice to employ a parametric approach, relates to the choice of a functional form for the production function.We choose a flexible functional form, the translog, which imposes fewer restrictions on elasticities of substitution than the Cobb–Douglas specification.

This can be specified as follows

$$\ln y_i = \sum_{k=1}^{K} \beta_k \ln X_{ki} + \frac{1}{2} \sum_{k=1}^{K} \sum_{l=1}^{K} \gamma_{kl} \ln X_{ki} \ln X_{li} \quad i = 1, 2, \ldots, N$$

where *y* and *X* again denote the technology transfer output and a vector of *K* technology transfer inputs, respectively, and *i* refers to the *i*th university. As before, we can append an error term, $\epsilon i = Vi - Ui$, to equation (4) and simultaneously estimate an equation representing the determinants of relative inefficiency *(Ui)*.

In the following section, we present the characteristics of our data and the econometric results.

4. Data and Empirical Results

Based on our previous discussion, we hypothesize the following three-factor, log-linear translog production function, where a measure of licensing activity is presumed to be a function of three inputs: invention disclosures, TTO staff, and legal expenditures:

$\ln(LICENSEi) = \beta 0 + \beta 1 \ln(INVDISCi) + \beta 2 \ln(STAFFi) + \beta 3 \ln(LEGALi)$

$+ \gamma 11(\ln(INVDISCi))2 + \gamma 22(\ln(STAFFi))2 + \gamma 33(\ln(LEGALi))2$

$+ \gamma 12 \ln(INVDISCi) \ln(STAFFi) + \gamma 23 \ln(STAFFi) \ln(LEGALi)$

$+ \gamma 31 \ln(LEGALi) \ln(INVDISCi) + Vi - UI$

where: *LICENSE* = average annual licensing agreements or revenue;

INVDISC = average annual invention disclosures;

STAFF = average annual TTO employees;

LEGAL = average annual external legal expenditures.

The technical inefficiency *Ui* term is expressed as

$$U_i = \theta_0 + \sum_k \theta_k \mathbf{ENV}_i + \sum_I \theta_I \mathbf{INST}_i + \sum_m \theta_m \mathbf{ORG}_i + \mu_i$$

where **ENV, INST,** and **ORG** are vectors of environmental, institutional, and organizational variables, respectively. Consistent with our discussion in the previous section regarding various proxies for these factors, the equation for *Ui* that we actually estimate is

$$Ui = \theta 0 + \theta \mathrm{M} MEDi + \theta \mathrm{RD} INDRDij + \theta \mathrm{Q} INDOUTij + \theta \mathrm{A1} AGEi + \theta \mathrm{A2} (AGEi)2$$

$$+ \theta \mathrm{A3} (AGEi)3 + \theta \mathrm{R} ROYALTYij + \theta \mathrm{S} STRUCTURE + \mu I$$

where *MED* is a dummy variable with a value of 1 if the university has a medical school; 0 otherwise, *INDRD* and *INDOUT* are average annual industry R&D intensity and average annual real output growth in the university's state (*j*), respectively, *AGE* is the age of the TTO, *ROYALTY* is the percentage of the royalty (or equity) that is allocated to faculty members who transfer technologies, *STRUCTURE* is a dummy variable with a value of 1 if the university has centralized licensing; 0 otherwise categorical variable describing how the university organizes its licensing activities, and μ is a classical disturbance term.

n the empirical analysis, two sets of (single output) production function estimates will be presented: one based on the average annual number of licensing agreements and another based on average annual licensing revenue. Our primary data source is a comprehensive survey conducted by AUTM, which was completed by TTO directors at 113 academic institutions for 1991–1998.12 The AUTM file contains annual data on the number of licensing agreements (LICENSE1), royalty income generated by licenses (LICENSE2), university startups generated (STARTUPS), invention disclosures (INVDISC), number of full-time-equivalent employees in the TTO (STAFF), and (external) legal expenditures on UITT (LEGAL). Our data sources for state-level industrial R&D (INDRD) and real output growth (INDOUT) are NSF and the BEA.13

A difficulty with two of the output measures (LICENSE1 and STARTUPS) is that they are count variables. For instance, licensing agreements vary substantially in their significance, which implies that it may be misleading to draw inferences about aggregate technology flows based on the number of deals.14 That is another reason why we consider licensing revenue as an additional measure of output, since it does not suffer from this problem.

Descriptive statistics and a correlation matrix for the inputs and outputs of the licensing production functions are presented in Table 2. The representative university in our sample consummates 16 licensing agreements per year, earns $1.9 million in licensing income, receives 56 invention disclosures, employs nine workers in the TTO, and spends $361,200 on external legal fees to protect its intellectual property. The correlation coefficients generally have the expected signs and magnitudes (e.g. invention disclosures are strongly positively correlated with the number of licensing agreements and revenue).

Table 2 Descriptive statistics and a matrix of correlation coefficients for the inputs and outputs of the stochastic frontier production function (equation (3))

Variable name	**Description**		**Mean**	**Median**	**Standard deviation**
LICENSE1	Average annual licensing agreements		16.1	9	22.1
LICENSE2	Average annual licensing revenue ($000)		1937.57	370	5101.3
INVDISC	Average annual invention disclosures		56.1	25	67.2
STAFF	Average annual TTO employees		9.4	5	16.3
LEGAL	Average annual external legal expenditures on UITT (000)		361.2	132.1	641.5

N=113 universities, 1991–1998.

Source: AUTM (1999).

Table 2 Descriptive statistics and a matrix of correlation coefficients for the inputs and outputs of the stochastic frontier production function (equation (3))

	LICENSE1	***LICENSE2***	***INVDISC***	***STAFF***	***LEGAL***
LICENSE1	1.00	0.88	0.64	0.49	−0.35
LICENSE2	0.88	1.00	0.67	−0.05	0.59
INVDISC	0.64	0.67	1.00	0.46	0.45
STAFF	0.49	−0.05	0.46	1.00	0.50
LEGAL	−0.35	0.59	0.45	0.50	1.00

Note that each variable is computed as an annual average over the sample period. Although it may desirable econometrically to construct a panel consisting of annual observations, this approach is problematic for two reasons. First, the use of annual data or lagged values to estimate the production function would result in an unbalanced panel, since all universities are not continuous reporters during the sample period. A related concern is that it is desirable to have a large sample of establishments when fitting the production function, given that the precision of this estimation will be highly dependent on the number of establishments used to project the frontier. Computing annual averages over the sample period yields the largest possible number of universities for the econometric estimation.

Table 3 contains two sets of parameter estimates of the stochastic frontier production function and inefficiency models outlined in the previous section (equations (5) and (7)) for two dependent variables: average annual number of licensing agreements and average annual licensing revenues, respectively.15 We used the FRONTIER statistical package (see Coelli, 1994) to generate these estimates. Columns (1) and (3) present maximum-likelihood estimates of without environmental, institutional, and organizational variables, while columns (2) and (4) present the coefficients of the stochastic frontier model including environmental, institutional, and organizational factors.

Table 3 Maximum likelihood parameter estimates of stochastic frontier translog production functions and determinants of relative inefficiency (equations (5) and (7))								
	Dependent variable							
	Average annual number of licensing agreements	**Average annual licensing revenue**						
Production function parameters	**(1)**	**(2)**	**(3)**	**(4)**				
β_0	−0.256*	(0.102)	−0.273**	(0.134)	1.887*	(0.803)	1.397**	(0.692)
β_1	0.652*	(0.104)	0.637*	(0.145)	1.245*	(0.452)	1.347*	(0.613)
β_2	0.467*	(0.093)	0.392*	(0.130)	−0.183	(0.297)	−0.184	(0.288)
β_3	−0.057**	(0.029)	−0.051**	(0.025)	0.395*	(0.138)	0.407*	(0.178)
γ_{11}	−0.010**	(0.004)	−0.009**	(0.004)	−0.014	(0.012)	−0.010	(0.006)
γ_{22}	−0.007	(0.005)	−0.010**	(0.004)	0.009	(0.011)	−0.012**	(0.006)
γ_{33}	−0.005	(0.008)	−0.011**	(0.005)	−0.010**	(0.004)	−0.005	(0.004)
γ_{12}	0.113**	(0.052)	0.065	(0.050)	0.085*	(0.038)	0.053	(0.046)

Table 3 Maximum likelihood parameter estimates of stochastic frontier translog production functions and determinants of relative inefficiency (equations (5) and (7))

	Dependent variable								
	Average annual number of licensing agreements	**Average annual licensing revenue**							
Production function parameters	**(1)**	**(2)**	**(3)**	**(4)**					
γ_{23}	−0.008	(0.010)	−0.008	(0.006)	−0.006	(0.008)	−0.006	(0.005)
γ_{31}	0.101*	(0.004)	0.007**	(0.003)	0.007	(0.008)	0.008	(0.011)
Determinants of relative inefficiency								
MED			−0.032	(0.068)			−0.006	(0.099)
INDRD			−0.084**	(0. 041)			−0.108**	(0.051)
INDOUT			0.007	(0.010)			−0.006	(0.020)
AGE			−0.070*	(0.032)			−0.076**	(0.037)
$(AGE)^2$			−0.051	(0.062)			0.064	(0.105)
$(AGE)^3$			0.093	(0.103)			−0.009	(0.012)

Table 3 Maximum likelihood parameter estimates of stochastic frontier translog production functions and determinants of relative inefficiency (equations (5) and (7))

	Dependent variable							
	Average annual number of licensing agreements	**Average annual licensing revenue**						
Production function parameters	**(1)**	**(2)**	**(3)**	**(4)**				
ROYALTY			−0.145**	(0.071)			−0.153**	(0.075)
STRUCTURE			0.038	(0.054)			−0.024	(0.042)
−log L	23.12		28.56		24.57		30.15	
	0.793*	(0.198)	0.694*	(0.292)	0.809*	(0.326)	0.751*	(0.283)
Mean technical								
efficiency	0.78		0.87		0.79		0.89	

Notes: Standard errors in parentheses, N=113 universities.

*Significant at the 1% level, **Significant at the 5% level.

We focus first on estimates of the production function parameters, which appear to be relatively stable, regardless of whether we include the determinants of relative inefficiency (columns (2) and (4)). Note that in all four variants of the model, β1, the elasticity of licensing output with respect to invention disclosures is estimated to be positive and highly statistically significant. In contrast, with respect to β2, we find that hiring additional staff in the TTO generates more agreements (columns (1) and (2)), but not additional revenue (columns (3) and (4)). Finally, our empirical estimates of β3 suggest that additional spending on outside lawyers (to negotiate licensing agreements) reduces the number of licensing agreements, but increases licensing revenue. This finding is consistent with our field research, where firms reported that it was much more difficult to negotiate with outside attorneys than university administrators. These same respondents reported that they would sometimes abandon negotiations with a school if they felt the lawyers were too aggressive in exercising its intellectual property rights. Each of these empirical results is consistent with those reported in our earlier study (Siegel et al., 2003), based on older data and a simpler econometric framework.

Next, we turn to the results regarding the determinants of relative inefficiency, based on the parameter estimates of equation (7), which appear in columns (2) and (4). It appears that an increase in industrial R&D within the same state as the university will enhance its licensing productivity (i.e. move that university closer to the ‘frontier’). The negative and significant coefficient on AGE implies that there may be organizational learning in UITT. It appears that our proxy for organizational incentives for UITT, ROYALTY, has the strongest impact on relative performance. That is, institutions that want to enhance UITT productivity should increase the share of licensing royalty payments allocated to faculty members. On the other hand, the insignificance of the coefficient on STRUCTURE is inconsistent with our hypothesis that decentralized technology transfer offices generate higher levels of performance.

Although several coefficients in Table 3 are insignificant, the γ values are highly statistically significant. This indicates that the null hypothesis that inefficiency effects are absent from the model can be decisively rejected in both equations. Further evidence that external factors generate considerable explanatory power is presented on the bottom of Table 3, which contrasts the mean technical efficiency in versions of the model excluding (columns (1) and (3)) and including (columns (2) and (4)) the environmental, institutional, and organizational variables. The latter set of findings indicates that these factors explain some of the variation in technical inefficiency across universities, 40.9% and 47.6%, respectively.16

5. Conclusions

Our findings imply that organizational incentives are an important factor in explaining why some universities outperform comparable institutions in transferring technologies, at least when licensing activity is considered to be the relevant ‘output’ of UITT. Recall that our empirical analysis focused exclusively on one dimension of the financial incentives for faculty members to engage in UITT. This result is consistent with the theoretical model presented in Beath et al.

2000), which suggests that faculty members respond to pecuniary incentives in deciding how to allocate effort to technology transfer activities. Universities that seek to enhance licensing should allocate a higher share of the royalties to faculty members. Stated alternatively, university administrators should view faculty as economic agents who respond to incentives. Changing incentives will change behavior.

It would be useful to extend our empirical analysis in three ways. First, we note that while faculty members are the key ‘suppliers’ in the production function model, incentives for university administrators may also be critical. That is, we also need to consider the importance of financial incentives for technology transfer officers, or those who manage the process of UITT. In this regard, it would be useful to examine whether universities where technology transfer officers receive some form of incentive compensation tend to be closer to the efficiency frontier.

A second extension would be to explore the role of non-pecuniary incentives, especially those relating to promotion and tenure policies at universities. These factors are clearly important determinants on the propensity of faculty members to engage in these activities. For instance, Lee (2000) reports that full professors are much more likely than assistant and associate professors to disclose inventions and patent.

Finally, we would also like to examine whether there are state-by-state differences in the determination of faculty salary adjustments at public universities. Such institutional controls should be explored, since they may serve as a proxy for the constraints that university administrators face when rewarding faculty for their commitment to technology licensing through the university.

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Notes

1. See Poyago-Theotoky et al. (2002) for an analysis of the policy implications of the growth of UITT.

2. We did not examine such hotbeds of UITT as Cambridge, Massachusetts (MIT, Harvard) or California's Silicon Valley (Stanford, UC-Berkeley), since we wish to explore this phenomenon at more representative institutions.

3. Detailed information on our qualitative methods is presented in Siegel et al. (2003).

4. Inventors often use such funds to support graduate students, post-doctoral fellows, and other laboratory costs.

5. These figures include expenditures in support of prosecution, maintenance, litigation, and interference costs related to patents and/or copyrights (see AUTM, 1999).

6. See Pressman et al. 1995).

7. This is especially problematic for public universities.

8. At some universities, there is a threshold effect, in the sense that inventors garner a very large share (e.g. 50%) at low levels of revenue (e.g. 50%), and then the share declines (e.g. 33%) as revenue exceeds a certain level. We thank Jonathan Silberman for providing us with these data.

9. Other distributional assumptions for the inefficiency disturbance that have been invoked are truncated normal and exponential (see Sena, 1999).

10. As discussed in Battese and Coelli (1995), this model can also incorporate panel data.

11. Thursby and Kemp (1998) and Thursby and Thursby (2000) use DEA to assess the relative efficiency of UITT.

12. The final sample contains 80 out of 89 Research One universities, or those that award 50 or more doctoral degrees and receive at least $40 million annually in federal research grants.

13. Source: NSF-Research and Development in Industry (1991–1996), U.S. BEA (1999)-Gross State Product data reported in Fixed Reproducible Tangible Wealth.

14. A similar problem is encountered with patents. Jaffe et al. (1993), Trajtenberg et al. (1997), and Henderson et al. (1998) weight patents on the basis of the number of citations they receive.

15. Although there is no direct diagnostic test for multi-collinearity, we do not observe any of the key symptoms of this problem: (1) High R 2 but few significant t ratios; (2) High pairwise and partial correlations among explanatory variables (see Table 2). Thus, we conclude that there does not appear to be a multi-collinearity problem.

16 That is, the average technical efficiency is closer to one when we include these variables in the stochastic frontier model $(0.09/(1 - 0.78) = 0.409$ and $0.10/(1 - 0.79) = 476)$.

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